

Energy Efficient Resource Allocation for Time-Varying OFDMA Relay Systems with Hybrid Energy Supplies

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Abstract—This paper investigates the energy efficient resource allocation for orthogonal frequency division multiple access (OFDMA) relay systems, where the system is supplied by the conventional utility grid and a renewable energy generator equipped with a storage device. The optimal usage of radio resource depends on the characteristics of the renewable energy generation and the mobile traffic, which exhibit both temporal and spatial diversities. Lyapunov optimization method is used to decompose the problem into the joint flow control, radio resource allocation and energy management without knowing a priori knowledge of system statistics. It is proven that the proposed algorithm can result in close-to-optimal performance with capacity limited data buffer and storage device. Simulation results show that the flexible tradeoff between the system utility and the conventional energy consumption can be achieved. Compared with other schemes, the proposed algorithm demonstrates better performance.

Index Terms—Cooperative relay, OFDMA, renewable energy, stochastic optimization.

I. INTRODUCTION

Orthogonal frequency division multiple access (OFDMA) is regarded as a promising technology in the future wireless communications, due to its advantages of high spectral efficiency and resistance to multipath fading. On the other hand, cooperative relaying is able to enhance the transmission range, system capacity and reliability. Thus, the relay-assisted OFDMA system has been attracting intensive research interests in both academia and industry since it can provide cooperative diversity, channel diversity and multiuser diversity gains at the same time.

Although the transmission quality of wireless systems can be improved with cooperative communications, the new challenges due to the dramatic increase of power cost and traffic demands in wireless communications have been increasingly prominent. About half of the mobile service provider's annual operating expenses are power costs and base stations (BSs) consume over 80% of the total energy of the network as claimed by Fehske *et al.* [1] and Feng *et al.* [2]. Moreover the largest fraction of greenhouse gas emissions caused by radio networks come from access networks, and mostly from BSs. Then the needs for energy saving of radio networks advocate

green radio communications. Green radio communications will not only help mobile operators to enhance the energy efficiency of BSs but also reduce the emissions of CO₂ by using renewable energy sources (*e.g.*, wind and solar power) to supply wireless communications in addition to the constant alternating current (AC) from utility grid, *e.g.*, the works by Ho *et al.* [3] and Niyato *et al.* [4]. As to the relay-assisted transmission powered by renewable energy source, like the idea of demand response in [5]- [8] the relay selection and radio resource allocation should be adaptive to the variations in harvested renewable energy in order to ensure the quality of service (QoS) of mobile users with the minimum AC energy. In addition, the joint design of relay selection, sub-carrier allocation and power control in relay-assisted OFDMA networks is a challenge since all the considered variables are coupled together, let alone the mentioned time-varying renewable energy generation.

In this paper, we consider a downlink OFDMA relay-assisted network consisting of multiple relay stations and a BS, which is powered by hybrid energy, *i.e.*, renewable energy and constant AC from the grid. Although the renewable energy provided by harvester is free, it is intermittent over time due to time-varying solar and wind patterns. In order to smooth the uncertain supply of renewable source, an energy storage device is equipped with the BS to buffer the intermittent renewable energy generation. Since the capacity of energy storage device and data buffer at the BS are finite, it is necessary to propose a joint design in order to coordinate the downlink transmission, radio resource allocation and energy management of the storage device in order to maximize the throughput utility with the least grid energy in a long-term manner. In summary, the contributions of this paper are as follows:

- From the perspective of network operator, we formulate a stochastic optimization problem to keep a balance between the throughput utility and on-grid energy consumption, which are usually two conflicting objectives.
- An online algorithm *FREE* is proposed to regulate the downlink data requests, allocate radio resource and manage energy in the storage device under the constraints of finite buffer size and storage capacity.
- The proposed *FREE* can arbitrarily approach the optimal tradeoff between system throughput and on-grid energy consumption by theoretic analysis and simulation results.

The rest of this paper is organized as follows. Section II

presents a review of related works. Section III describes the system model and the components of the system. Section IV casts the problem into a stochastic optimization problem. Section V presents an online algorithm to jointly allocate resource and manage energy. Section VI analyzes the performance of the proposed algorithm. Simulations are provided in Section VII. The paper is concluded in Section VIII.

II. RELATED WORKS

Since this paper considers the scenario of relay-based cooperative networks with hybrid energy supply, the related works on cooperative communications are first reviewed and then some latest results on renewable energy powered communications are discussed.

Various cooperative communication schemes such as Amplify-and-Forward (AF) and Decode-and-Forward (DF) have been proposed in the literature [9]- [21]. Compared with a DF relay decoding, re-modulating and retransmitting the received signal, an AF one simply amplifies and retransmits the signal towards destinations without decoding. Wang *et al.* in [10] and Shen *et al.* in [11] proposed power control for fairness in AF relay networks. The power control of multiple users with AF relays are considered by Zappone *et al.* in [12] and by Cheung *et al.* in [13] for energy-efficiency. Depending on the channel condition and performance criterion, DF may outperform AF, or vice versa. For DF relay strategy, [14]- [18] considered the resource allocation by solving a class of static optimization problem. The joint design of congestion control and relay resource allocation for LTE-A was proposed in [19] by solving a stochastic optimization problem. Tang *et al.* in [20] proposed three greedy algorithms for multiuser multiple relay networks to maximize the network utility and comprehensive theoretical analysis was given to measure the worst performance. Different from the assumption of half-duplex at relay, Li *et al.* in [21] proposed a full-duplex cooperative communication scheme. In this paper, the energy-aware relay-assisted transmission aims to balance the throughput utility and on-grid energy consumption. Since the transmission power of relays is coupled with the power allocation of the BS, which is supplied by hybrid energy, the relay power allocation, transmission mode selection (cooperative transmission or direct transmission) and subcarrier allocation are all affected by queue states, residual energy in storage device. This makes the radio resource allocation problem significantly different from the aforementioned works.

To reduce the consumption of on-grid energy in wireless access networks, there are some works considering that the transmitter is powered by hybrid energy source [22]- [24]. This paper considers that the transmitter is also powered by hybrid energy source in a relay-assisted cooperative communication scenario, where an online joint resource allocation and energy management algorithm is proposed with lower computational complexity compared with the dynamic programming based ones in [22]- [23]. Compared against [24] the salient feature of the proposed algorithms in this paper is that its implementation is independent of the energy harvesting profiles. For the delay/throughput optimal transmission with renewable energy

sources, the schemes on transmission power control and energy management in battery for point-to-point transmissions were proposed in [25]- [27]. The network planning problem with sustainable energy sources in OFDMA relay networks was considered by Zheng *et al.* in [28] to ensure network connectivity and users' QoS requirements. To further reduce the circuit energy consumption of cellular networks, the BSs or relay stations (RSs) can be switched into sleep mode dynamically by utilizing the spatial and temporal fluctuations of traffic loads and inter-cell cooperation [29]- [33]. The most related work also includes [34], where Ahmed *et al.* consider power control for a cooperative system consisting of one energy harvesting (EH) source and one EH relay communicating to one destination. Almost all the above works assume that either the data buffer or the storage device is infinite to make their problem tractable. Also the prior knowledge on random events is needed in their designs. In this paper, the trade-off between throughput utility and grid energy consumption is considered for multi-user/multi-relay networks under the constraints of finite data and energy buffer. An online algorithm is designed without relying on any statistical information.

III. SYSTEM MODEL

A. Physical Layer Model

We consider the downlink transmission in a two-hop relay-assisted network, which consists of a set of users $\mathcal{N} = \{1, 2, \dots, N\}$ indexed by n , a set of RSs $\mathcal{R} = \{1, 2, \dots, K\}$ indexed by i and one BS indexed by B . OFDMA is employed over both hops and the whole bandwidth W is equally divided into M subcarriers with sub-bandwidth $b = \frac{W}{M}$. The set of subcarriers is $\mathcal{M} = \{1, 2, \dots, M\}$ and the subcarrier is indexed by m . The noise at each receiver on each subcarrier is zero-mean circular symmetric complex Gaussian with variance bN_0 . The system is assumed to be a time-slotted one with equal time interval normalized to be unit time. Hereafter b is assumed to be one without loss of generality.

The BS can transmit directly to each user or employ one of the RSs for cooperative communications. If the cooperative communication is adopted, each transmission consists of two stages. In the first stage, the BS communicates with RSs and users on some subcarriers. In the second stage, the selected RS on the same subcarriers helps the BS transmit to the user with decode-and-forward (DF) strategy¹ with the same codebook as that of the BS. Let $\{\alpha_{i,n}^m : \alpha_{i,n}^m \in \{0, 1\}, \forall n \in \mathcal{N}, i \in \mathcal{R}, m \in \mathcal{M}\}$ denote the set of RS, user and subcarrier matching indicator, where $\alpha_{i,n}^m = 1$ indicates that the BS can communicate with user n via relay i over the m^{th} subcarrier, and $\alpha_{i,n}^m = 0$ otherwise. Note that $\alpha_{B,n}^m = 1$ means that the BS will communicate to user n over subcarrier m directly and $\alpha_{B,n}^m = 0$ otherwise. An exclusive subcarrier assignment is enforced such that at most one user or one user-relay pair can be allocated to a single subcarrier. Also, on one subcarrier,

¹The performance of DF outperforms AF depending on channel conditions and performance criterion. In this paper, we only consider DF strategy. The similar technique can be applied to AF relay.

only one transmission mode (cooperative or direct) is allowed. These constraints are as follows, $\forall n \in \mathcal{N}, i \in \mathcal{R}, m \in \mathcal{M}$

$$\sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{R}} (\alpha_{i,n}^m + \alpha_{B,n}^m) \leq 1, \quad \alpha_{i,n}^m \in \{0, 1\}, \alpha_{B,n}^m \in \{0, 1\}. \quad (1)$$

We use $c_{B,n}^m$ to denote the achievable rate by the BS transmitting to user n directly over the m^{th} subcarrier. We have

$$c_{B,n}^m = \log_2 \left(1 + \frac{p_B^m |h_{B,n}^m|^2}{\Gamma N_0} \right)$$

where p_B^m denotes the BS's transmission power on the m^{th} subcarrier and $h_{B,n}^m$ is the channel gain from the BS to user n over subcarrier m . Γ is the gap to Shannon capacity, which is mainly determined by modulation techniques and the target bit-error rate. When the BS is communicating with user n assisted by RS i over the m^{th} subcarrier, the achievable rate is given by [35],

$$c_{i,n}^m = \frac{1}{2} \min \left\{ \log_2 \left(1 + \frac{p_B^m |h_{B,i}^m|^2}{\Gamma N_0} \right), \log_2 \left(1 + \frac{p_B^m |h_{B,n}^m|^2 + p_{i,n}^m |h_{i,n}^m|^2}{\Gamma N_0} \right) \right\} \quad (2)$$

where " $\frac{1}{2}$ " in (2) is due to the half duplex forward constraint, $h_{B,i}^m$ is the channel gain from the BS to RS i on subcarrier m , $h_{i,n}^m$ is the channel gain from RS i to user n on the m^{th} subcarrier and $p_{i,n}^m$ is the allocated relay power by RS i for user n over the m^{th} subcarrier. For notational simplicity we define $H_{B,n}^m \triangleq |h_{B,n}^m|^2 / \Gamma N_0$, $H_{B,i}^m \triangleq |h_{B,i}^m|^2 / \Gamma N_0$, $H_{i,n}^m \triangleq |h_{i,n}^m|^2 / \Gamma N_0$, ($\forall n \in \mathcal{N}, i \in \mathcal{R}, m \in \mathcal{M}$) as the normalized channel gains for the rest of the paper. We use $\mathcal{I}(t) = \{H_{B,n}^m(t), H_{B,i}^m(t), H_{i,n}^m(t) : \forall n \in \mathcal{N}, i \in \mathcal{R}, m \in \mathcal{M}\}$ to denote the collection of all the channel state information at time slot t . It is assumed that $\mathcal{I}(t)$ belongs to a finite space that has arbitrarily large size and is independent and identically distributed (i.i.d.) at every slot. Considering the BS may communicate with user n directly or with the assistance of selected relay over some subcarriers, the transmission rate for user n is

$$\mu_n(t) = \sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{R}} (\alpha_{i,n}^m c_{i,n}^m + \alpha_{B,n}^m c_{B,n}^m) \quad (3)$$

Denote p_B^{\max} and p_i^{\max} as the total transmission power constraint for the BS and RSs, respectively, i.e.,

$$p_B \leq p_B^{\max}, \quad p_i \leq p_i^{\max}, \quad \forall i \in \mathcal{R}, \quad (4)$$

where $p_B = \sum_{m \in \mathcal{M}} p_B^m$, $p_i = \sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{M}} p_{i,n}^m$. In addition, there are the power mask constraints $\hat{P}(m)^2$ on each subcarrier for the BS and RSs to avoid the adjacent cell interference, i.e.,

$$0 \leq p_B^m \leq \hat{P}(m), \quad 0 \leq p_{i,n}^m \leq \hat{P}(m). \quad (5)$$

²In reality, the power mask should be location-dependent and each RS and BS should have different mask even over the same subcarrier. Here for easy expression, we use the same power mask for all RSs and BS over the same subcarrier. To avoid trivial solutions, it is assumed that $\sum_{m \in \mathcal{M}} \hat{P}(m) > p_B^{\max}$, $N \sum_{m \in \mathcal{M}} \hat{P}(m) > p_i^{\max}$, $\forall i \in \mathcal{R}$.

The determination of $\hat{P}(m)$ is out of the scope of this paper and is given a priori.

B. Queueing Model

At the BS there are random arrival packets with rate $A_n(t)$ packets/slot at the end of time slot t waiting for transmission to user n . Each user's packets are stored in one of N data queues corresponding to each destination before they can be sent out. The packet arrival process $A_n(t) \in [0, A_n^{\max}]$ is assumed to be i.i.d over each time slot and $\mathbb{E}[A_n(t)] = \lambda_n$, $\forall n \in \mathcal{N}$. Among the arrival packets, only $R_n(t)$ of $A_n(t)$ are admitted into each user's buffer with queue length $Q_n(t)$ in time slot t by a flow control mechanism. The data queue is updated as

$$Q_n(t+1) = [Q_n(t) - \mu_n(t)]^+ + R_n(t), \quad \forall n \in \mathcal{N}, \quad (6)$$

where $[x]^+ = \max\{0, x\}$, and $\mu_n(t)$ is the service rate of user n given in (3). To quantitatively measure the balance between the transmission request $R_n(t)$ and service rate $\mu_n(t)$, the definition of stability is given first.

Definition 1 ([38]): A queue $Q(t)$ is strongly stable if:

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{Q(\tau)\} < \infty$$

A network is strongly stable if all individual queues of the network are strongly stable.

In the following, strong stability is also referred to stability.

C. Energy Management Model

Actually, the power consumption of BS or RSs consists of two parts. One part is the dynamic transmission power of the power amplifier denoted as p and the other part is Δp , the static power consumption of the radio frequency chains including power dissipation in the mixer, transmit filters and digital-to-analog converters [23] [27]. Thus the power consumption of the BS and relay i can be expressed as $P_B = p_B + \Delta p_B$ and $P_i = p_i + \Delta p_i$, respectively. Since the BS dominates the energy consumption in cellular networks [36], its required energy can be taken not only from the renewable energy generator but also from the power grid. Due to the investment cost each RS is only powered by grid. To "smooth" the intermittent renewable energy supply, we introduce an energy storage device to the BS. The harvested renewable energy is first put into the storage device and then withdrawn to supply the BS. If the residual energy in the storage is not enough, the BS will be supplied by the grid. Since the storage device has a limited size, we have to cope with charging and discharging properly. Let $w(t)$ with $w(t) \in [0, w^{\max}]$ denote the harvested energy from the renewable source at time slot t . Only $\delta(t)w(t)$ of the renewable energy is actually charged into the storage device, where $\delta(t) \in [0, 1]$. The energy level $S(t)$ at the storage device is updated as an energy queue [37]:

$$S(t+1) = S(t) - O(t) + \delta(t)w(t), \quad (7)$$

where $O(t)$ is the total power withdrawn from the storage device to supply the BS at time slot t . As it can be found later, the energy management of the BS is designed based on $S(t)$

TABLE I
NOTATIONS

Symbol	Definition
$\mathcal{N} = \{1, \dots, N\}$	Set of users
$\mathcal{R} = \{1, \dots, K\}$	Set of RSs
$\mathcal{M} = \{1, \dots, M\}$	Set of subcarriers
$\alpha_{B,n}^m, \alpha_{i,n}^m$	Subcarrier allocation indicator
$c_{B,n}^m, c_{i,n}^m$	Direct and cooperative transmission rates
$H_{B,n}^m, H_{B,i}^m, H_{i,n}^m$	Normalized channel gains
$\mathcal{I}(t)$	Collection of all channel states
$\mu_n(t)$	Transmission rate for user n
p_B^m	Transmission power of BS over subcarrier m
$p_{i,n}^m$	Transmission power of RS over subcarrier m
$X_n(t), R_n(t)$	Potential admitted rate and actual admitted rate
$Q_n(t)$	Queue length of user n at BS
$U_n(t)$	Virtual queue length of user n at BS
$S(t)$	Energy level at BS storage device
$O(t)$	Withdraw power from storage device
$\omega(t), \delta(t), \omega(t)$	Harvested and actual stored renewable energy
$J(t)$	Energy drawn from the grid to supply BS

instead of the profile of $w(t)$. There is a maximum discharge rate constraint O^{\max} for the storage device. The energy level in the storage device should be always available and can not exceed the storage capacity S^{\max} . Therefore, at each time slot, we should ensure that

$$O(t) \leq \min \{S(t), O^{\max}\}. \quad (8)$$

$$w(t) \leq \min \{w^{\max}, S^{\max} - S(t)\}. \quad (9)$$

The BS's power consumption $P_B(t)$ is supplied by $O(t)$ from the storage device and $J(t)$ from power grid directly with $0 \leq J(t) \leq J^{\max}$, i.e.,

$$P_B(t) = O(t) + J(t). \quad (10)$$

J^{\max} is used to take into account the hardware and line constraint of BS power supply system. Thus the total energy withdrawn from the power grid at time slot t is $P(t) = J(t) + \sum_{i \in \mathcal{R}} P_i(t)$. For the BS being able to be supplied by storage device or power grid independently, it is assumed that $J^{\max} \geq p_B^{\max} + \Delta p_B$ and $O^{\max} \geq p_B^{\max} + \Delta p_B$. The important notations of this paper are listed in Table I.

IV. PROBLEM FORMULATION

The objective of the network operator is to maximize the total utility of the average throughput for each user with the least on-grid energy consumption. Here the utility function $f(\cdot)$ is assumed to be non-decreasing, non-negative and concave, which is used to maintain fairness in resource allocation [38]. Since there are some random events in the system, such as random arrival packets towards each user and renewable energy generation, it is more reasonable to optimize the objective in a long-term manner. Basically the system stability should be maintained. Since the maximum system utility and the least on-grid energy consumption are usually two conflicting objectives, we will find a policy to solve the following stochastic optimization problem to achieve optimal tradeoff between them,

$$(P1) \quad \begin{aligned} \max \quad & \phi \sum_{n \in \mathcal{N}} f(\bar{R}_n) - \varphi \bar{P} \\ \text{s.t.} \quad & \text{C1: } \bar{R}_n \leq \lambda_n, \forall n \in \mathcal{N} \\ & \text{C2: } (1), (4), (5), (7), (8), (9), (10), \forall t \\ & \text{C3: the system is stable} \end{aligned}$$

where

$$\bar{R}_n \triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{R_n(\tau)\}$$

is the time-average admitted rate of user n , and

$$\bar{P} \triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{P(\tau)\}$$

is the time-average on-grid energy consumption and the expectations are taken with respect to the random events. ϕ and φ are two constants introduced to make a tradeoff between throughput utility and on-grid energy consumption. Denote the optimal objective value of (P1) as \mathcal{V}_1 . Due to C1 and the bounded on-grid energy consumption, we can always find a constant \mathcal{V}^{\max} such that $\mathcal{V}_1 \leq \mathcal{V}^{\max}$. In (P1) if $f(\bar{R}_n)$ is chosen as \bar{R}_n , the objective function of (P1) is also known as the parametric form in solving the energy efficiency maximization problem [40].

In problem (P1), the current energy management policy is coupled with future ones due to the iteration (7), i.e., the current energy management policy may have impacts on the future energy charging or discharging action for the energy storage device. This coupling nature together with unknown statistics of renewable energy generation makes (P1) difficult. Denote $\bar{O} \triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{O(\tau)\}$, $\bar{\delta} \bar{w} \triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{\delta(\tau) w(\tau)\}$ as the time-average value of the expected energy withdrawn from the storage device and the input renewable energy, respectively. By summing (7) from the initial state to $t-1$ and taking expectations on both sides, we have

$$\mathbb{E} \{S(t)\} - S(0) = \sum_{\tau=0}^{t-1} \mathbb{E} \{-O(\tau) + \delta(\tau) w(\tau)\}. \quad (11)$$

Since the energy level in the storage device satisfies $0 \leq S(t) \leq S^{\max}$, we have $\bar{O} = \bar{\delta} \bar{w}$ after dividing both sides of (11) by t and taking limitation of $t \rightarrow \infty$. Since the objective function of (P1) is a function of the time average, to make it tractable we transfer it to an optimization problem with a time averaged objective function. We instead consider (P2) to tackle the time-coupling difficulties in (7) and the objective function in (P1).

$$(P2) \quad \begin{aligned} \max \quad & \phi \sum_{n \in \mathcal{N}} \overline{f(X_n)} - \varphi \bar{P} \\ \text{s.t.} \quad & \text{C1': } \bar{X}_n \leq \bar{R}_n, \forall n \in \mathcal{N} \\ & \text{C2': } X_n(t) \leq A_n^{\max}, \forall t, n \in \mathcal{N} \\ & \text{C3': } (1), (4), (5), (9), (10), \forall t \\ & \text{C3: the system is stable} \\ & \text{C4: } \bar{O} = \bar{\delta} \bar{w} \end{aligned}$$

where $X_n(t)$ is an auxiliary variable, and $\overline{f(X_n)} \triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{f(X_n(t))\}$, $\bar{X}_n \triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{X_n(t)\}$, which can be understood as the lower bound of \bar{R}_n as shown in C1'. In the following section, we will use virtual queue technique to satisfy the time average constraint C1'. Denote the optimal objective value of (P2) as \mathcal{V}_2 . By Ch5 of [39], we have $\mathcal{V}_2 \geq \mathcal{V}_1$. Now, there is no time correlation on the energy level of storage device in (P2). Using the theory of Lyapunov optimization,

(P2) can be solved by an online algorithm to achieve the close-to-optimal performance subject to system stability.

V. JOINT FLOW CONTROL, RESOURCE ALLOCATION AND ENERGY MANAGEMENT

Since the buffer size at the BS is finite, to ensure that each data queue $Q_n(t)$ at the BS has a deterministic upper bound Q_n^{\max} with $Q_n^{\max} \geq A_n^{\max}$, where $A_n^{\max} = \max_n \{A_n^{\max}\}$, we introduce the following virtual queue,

$$U_n(t+1) = [U_n(t) - R_n(t)]^+ + X_n(t), \quad \forall n \in \mathcal{N} \quad (12)$$

whose stability can satisfy the constraint C1' in (P2).

It is observed that in (P2), the decision variables $\{R_n(t)\}$, $\{\alpha_{B,n}^m, \alpha_{i,n}^m(t)\}$, $\{P(t)\}$, $\{O(t)\}$ and $\{\delta(t)\}$ are coupled together. We decompose the system problem (P2) into joint Flow control, Resource allocation and Energy management (*FREE*) by Lyapunov optimization method in each time slot. Its design principle is to minimize the upper bound of Lyapunov drift minus system objective function greedily without knowing the profile of stochastic events. The detailed derivation can be found in the proof of Theorem 9. Fig. 1 illustrates that the coupled dynamics in *FREE* are coordinated by queue states $\{U_n(t), X_n(t), S(t)\}$. Although *FREE* are designed to solve (P2) online and separately, Theorem 9 demonstrates that it can approach the optimal solution of (P1) asymptotically. Its detailed design is as follows. In the following, the joint flow control, wireless resource allocation and energy management in *FREE* will be described in detail.

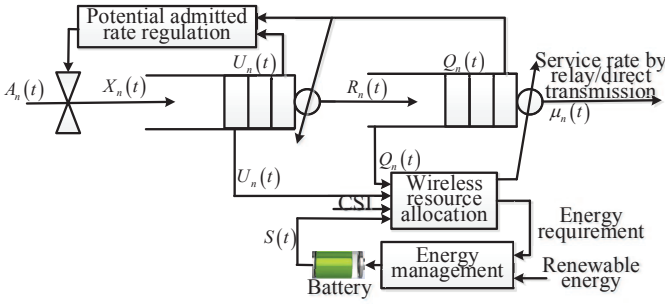


Fig. 1. Diagram of coupled problems of flow control, wireless resource allocation and energy management.

A. Flow Control

At each time slot t , the BS decides the admission data rate $\{R_n(t)\}$ to the data buffer of each user as the solution to the following problem,

$$\begin{aligned} \min_{R_n(t)} \quad & R_n(t) (Q_n(t) - Q_n^{\max} + A_n^{\max}) \\ \text{s.t.} \quad & 0 \leq R_n(t) \leq A_n(t) \end{aligned} \quad (13)$$

The problem (13) is corresponding to one part of the upper bound of Lyapunov drift plus penalty in (38). The solution to the above problem is

$$R_n(t) = \begin{cases} 0 & \text{if } Q_n(t) > Q_n^{\max} - A_n^{\max} \\ A_n(t) & \text{otherwise} \end{cases} \quad (14)$$

In (14), the tradeoff between system utility and on-grid energy is not explicitly considered. It can be intuitively understood that more saved on-grid energy will result in a smaller $\mu_n(t)$ and a larger $Q_n(t)$ subsequently by (6). Then according to (14), more arrival packets will be dropped in order to mitigate congestion. Thus, on-grid energy is saved with a compromise of throughput.

The potential admitted rate $X_n(t)$ is the solution to the following problem,

$$\begin{aligned} \min_{X_n(t)} \quad & \frac{Q_n^{\max} - A_n^{\max}}{Q_n^{\max}} U_n(t) \cdot X_n(t) - V \phi f(X_n(t)) \\ \text{s.t.} \quad & 0 \leq X_n(t) \leq A_n^{\max} \end{aligned} \quad (15)$$

If $f(\cdot)$ is differentiable, $X_n(t)$ is updated as

$$X_n(t) = \min \left\{ \max \left\{ 0, f'^{-1} \left(\frac{Q_n^{\max} - A_n^{\max}}{Q_n^{\max} V \phi} U_n(t) \right) \right\}, A_n^{\max} \right\}, \quad (16)$$

where $V \geq 0$ is a parameter set according to the system performance requirement and is to be specified in Section VI.

B. Wireless Resource Allocation

We determine the power control, RS selection and subcarrier allocation by solving the following optimization problem based on the measurement of channel states and queue states at the beginning of each time slot.

$$\begin{aligned} \max \quad & \sum_{n \in \mathcal{N}} \left(\frac{U_n(t) Q_n(t)}{Q_n^{\max}} \mu_n(t) + (S(t) - \theta) p_B(t) \right) \\ & - V \varphi \sum_{i \in \mathcal{R}} p_i(t) \\ \text{s.t.} \quad & (1), (4), (5) \end{aligned} \quad (17)$$

The optimization problem (17) has zero-duality-gap if the number of subcarrier goes to infinity [41] [42]. We introduce the Lagrange multipliers λ_i and λ_B to relax the power constraints (4) and solve (17) by Lagrangian dual decomposition. The Lagrange function is

$$\begin{aligned} L(\alpha, \mathbf{p}, \lambda) \\ = \sum_{n=1}^N \left(\frac{U_n(t) Q_n(t)}{Q_n^{\max}} \mu_n(t) + (S(t) - \theta) p_B(t) \right) \\ - V \varphi \sum_{i=1}^K p_i(t) + \lambda_B (p_B^{\max} - p_B(t)) + \sum_{i=1}^K \lambda_i (p_i^{\max} - p_i(t)). \end{aligned} \quad (18)$$

The dual function is $D(\lambda) = \max_{\alpha, \mathbf{p}} L(\alpha, \mathbf{p}, \lambda)$ ³, which can be decomposed into M independent subproblems,

$$\begin{aligned} \max \quad & \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{R}} \Omega_m \\ \text{s.t.} \quad & (5), \quad \forall m \in \mathcal{M}, \end{aligned} \quad (19)$$

where

$$\begin{aligned} \Omega_m \\ = \frac{U_n Q_n}{Q_n^{\max}} \alpha_{B,n}^m c_{B,n}^m(t) + \alpha_{B,n}^m (S(t) - \theta - \lambda_B) p_B^m(t) \\ \triangleq \Omega_m(B, n) \end{aligned} \quad (20)$$

³Hereafter, we use bold letter to denote a vector, e.g., $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_K, \lambda_B]$.

if direct transmission towards user n is adopted over subcarrier m , or

$$\begin{aligned} & \Omega_m \\ &= \frac{U_n Q_n}{Q_{\max}} \alpha_{i,n}^m c_{i,n}^m(t) + \alpha_{i,n}^m (S(t) - \theta - \lambda_B) p_B^m(t) \\ & \quad - \alpha_{i,n}^m (V\varphi + \lambda_i) p_{i,n}^m(t) \\ & \triangleq \Omega_m(i, n), \end{aligned} \quad (21)$$

if relay-assisted transmission is chosen.

We first consider the direct transmission (20) to find the optimal $\Omega_m^*(B, n)$,

$$\max_{0 \leq p_B^m \leq \bar{P}(m)} \frac{U_n(t) Q_n(t)}{Q_{\max}} c_{B,n}^m(t) + (S(t) - \theta - \lambda_B) p_B^m(t).$$

The optimal transmission power of the BS over subcarrier m is obtained as

$$p_B^m(t) = \begin{cases} \hat{p}_B^m(t) & \text{otherwise} \\ \bar{P}(m) & \text{if } \theta + \lambda_B - S(t) \leq 0 \end{cases}, \quad (22)$$

where $\hat{p}_B^m(t) = \left(\frac{U_n(t) Q_n(t)}{Q_{\max}(\theta + \lambda_B - S(t)) \log 2} - \frac{1}{H_{B,n}^m} \right)_0^{\bar{P}(m)}$ and $(x)_a^b = \min\{b, \max\{a, x\}\}$. In the case of $\theta + \lambda_B - S(t) > 0$, $p_B^m(t)$ in (22) is obtained by solving the derivative of $\Omega_m(B, n)$ to $p_B^m(t)$ being equal to zero. After substituting (22) into (20) we can obtain the optimal $\Omega_m^*(B, n)$ given that the BS transmits to user n over subcarrier m directly.

In the case of cooperative transmission, we consider the following two cases (23) and (24) for the objective function (21).

$$\begin{aligned} \max & \quad q_n(t) \log(1 + p_B^m H_{B,n}^m + p_{i,n}^m H_{i,n}^m) \\ & \quad + (S(t) - \theta - \lambda_B) p_B^m - (V\varphi + \lambda_i) p_{i,n}^m \\ \text{s.t.} & \quad p_B^m H_{B,i}^m > p_B^m H_{B,n}^m + p_{i,n}^m H_{i,n}^m \\ & \quad 0 \leq p_B^m(t) \leq \bar{P}(m), \quad 0 \leq p_{i,n}^m(t) \leq \bar{P}(m) \end{aligned}, \quad (23)$$

$$\begin{aligned} \max & \quad q_n(t) \log(1 + p_B^m H_{B,i}^m) \\ & \quad + (S(t) - \theta - \lambda_B) p_B^m - (V\varphi + \lambda_i) p_{i,n}^m \\ \text{s.t.} & \quad p_B^m H_{B,i}^m \leq p_B^m H_{B,n}^m + p_{i,n}^m H_{i,n}^m \\ & \quad 0 \leq p_B^m(t) \leq \bar{P}(m), \quad 0 \leq p_{i,n}^m(t) \leq \bar{P}(m) \end{aligned}, \quad (24)$$

where $q_n(t) = \frac{U_n(t) Q_n(t)}{2Q_{\max} \log 2}$.

Theorem 2: The optimal transmission power allocation for problem (23) is as follows:

- If $S(t) - \theta - \lambda_B + \frac{(V\varphi + \lambda_i) H_{B,n}^m}{H_{i,n}^m} \geq 0$, $p_B^m(t) = \bar{P}(m)$, $p_{i,n}^m(t) = \left(\frac{d_{i,n}^m - \bar{P}(m) H_{B,n}^m}{H_{i,n}^m} \right)^+$, where $d_{i,n}^m = \max\{0, \min\{\frac{q_n(t) H_{i,n}^m}{V\varphi + \lambda_i} - 1, \bar{P}(m) H_{B,i}^m, \bar{P}(m) H_{i,n}^m + \bar{P}(m) H_{B,n}^m\}\}$.
- If $S(t) - \theta - \lambda_B + \frac{(V\varphi + \lambda_i) H_{B,n}^m}{H_{i,n}^m} < 0$, $p_B^m(t) = p_{i,n}^m(t) = 0$.

The optimal solution to problem (24) is

- If $H_{B,i}^m > H_{B,n}^m$, $p_B^m(t) = p_{i,n}^m(t) = 0$.
- If $H_{B,i}^m \leq H_{B,n}^m$, $p_{i,n}^m(t) = 0$, $p_B^m(t) = \begin{cases} \bar{P}(m) & \text{if } S(t) - \theta - \lambda_B \geq 0 \\ \left(\frac{q_n(t)}{\lambda_B - S(t) + \theta} - \frac{1}{H_{B,i}^m} \right)_0^{\bar{P}(m)} & \text{otherwise} \end{cases}$.

Proof: The proof can be found in Appendix A. ■

Some intuitive explanations for *Theorem 2* are given below.

Remark 3: For the solution to problem (23), it can be found that in the case of $S(t) - \theta - \lambda_B + \frac{(\varphi + \lambda_i) H_{B,n}^m}{H_{i,n}^m} \geq 0$ if the second hop channel gain $H_{i,n}^m$ is relatively low compared with $H_{B,n}^m$, which may result in $d_{i,n}^m = 0$, the BS will ask no relay for help transmission to avoid more electricity withdrawn from power grid to supply the relay. Moreover, for the same case, if $q_n(t)$ is large enough, which may result in a large $d_{i,n}^m$, the BS has to ask relay i for helping transmission to alleviate congestion of user n 's buffer. In the aforementioned situation, the BS transmits with $\bar{P}(m)$ since there is enough residual energy in the storage device and the objective function of (23) is increasing with respect to p_B^m . If $S(t) - \theta - \lambda_B + \frac{(\varphi + \lambda_i) H_{B,n}^m}{H_{i,n}^m} < 0$ due to less residual energy in the storage device, the combination of relay i , the BS and user n is not suitable for transmission over subcarrier m to avoid withdrawing too much electricity from the grid.

Remark 4: By the above description, it may be concluded some subcarriers will be abandoned temporarily due to their low energy efficiency. At the same time the abandoned subcarriers can be used by other cells belonging to the same operator. The abandoned subcarriers can also be re-used by the same cell after a while when the channel conditions turn to be better. Therefore, the network operator will not waste any resource or revenue from a long term and global point of view.

By substituting the optimal transmission power in *Theorem 2* to (21) the optimal $\Omega_m^*(i, n)$ is obtained. Then the subcarrier allocation and relay selection can be achieved by

$$\begin{aligned} & \alpha_{j,n}^m \\ &= \begin{cases} 1 & \text{if } (j, n) = \arg \max_{j \in \{B\} \cup \mathcal{R}, n \in \mathcal{N}} \{\Omega_m^*(i, n), \Omega_m^*(B, n)\} \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (25)$$

Note that in (25) j can be the index of a RS or referred to the BS if direct transmission is adopted.

The associated dual problem of (17) is $\min_{\lambda \geq 0} D(\lambda)$, which can be solved by standard subgradient method (26) and (27), $\forall i \in \mathcal{R}$.

$$\begin{aligned} & \lambda_B(k+1, t) \\ &= \left[\lambda_B(k, t) + \varsigma_k \left(\sum_{m=1}^M p_B^m(k, t) - p_B^{\max} \right) \right]^+ \end{aligned} \quad (26)$$

$$\begin{aligned} & \lambda_i(k+1, t) \\ &= \left[\lambda_i(k, t) + \varsigma_k \left(\sum_{n=1}^N \sum_{m=1}^M \alpha_{i,n}^m p_{i,n}^m(k, t) - p_i^{\max} \right) \right]^+, \end{aligned} \quad (27)$$

where k is the iteration index in time slot t , $[x]^+ \triangleq \max\{0, x\}$ and ς_k is step size at the k^{th} iteration. The convergence of (26) and (27) can be guaranteed by a diminishing step size ς_k [43].

Remark 5: In practice, the subproblems (23) and (24) are solved by each RS locally for NM times during one iteration k and the computational complexity at each relay is $O(NM)$, which is the same as [41]. And then each relay transmits the optimal $\Omega_m^*(i, n)$ to the BS for the final subcarrier allocation.

The deployment of a certain amount RSs to proper place is also important in utilizing the cooperative diversity and has been extensively investigated in [28] and [31]. A candidate place is where a RS can not only serve users better than direct transmission but also be easy to access on-grid power. Candidate place can be the roof of a building, where RSs serve users in the building. Thus the number of candidate places in a considered area is finite. Since the joint deployment of RS and resource allocation problem is NP-hard, heuristic algorithm will be considered. Firstly, all candidate places are deployed with RSs. Users requiring relay are associated to the RS with the minimum *RTE* which is defined as the quotient of user's throughput requirement and achievable throughput with unit transmission power and subcarrier. Then subcarriers are allocated among RSs and BS to satisfy each user's throughput requirement proportionally. The transmission power of BS and RSs can be obtained by waterfilling. Secondly, calculate each RS's energy efficiency value, which is defined as the total achievable throughput divided by the RS's energy consumption. Sort all RSs in an ascending order based on its energy efficiency value. Thirdly, try to delete the first RS from and candidate place and re-connect its users to other RSs based on the *RTE* criterion in the first step. Subcarriers and transmission power are re-allocated. If each user's throughput requirement is satisfied, try to delete the second RS and repeat. If the removal of the $(k+1)^{\text{th}}$ RS cannot satisfy users throughput requirements, the algorithm outputs the deployment of k RSs in the last round. Due to space limitation, we do not evaluate the heuristic RS placement. Its idea is similar with [28], which has demonstrated good performance with low time complexity.

C. Energy Management

At each time slot t , the BS manages the energy level in its storage device based on local information by solving the following problem:

$$\begin{aligned} \min_{J, \delta} \quad & (\varphi V + S(t) - \theta) J(t) + (S(t) - \theta) \delta(t) w(t) \\ \text{s.t.} \quad & (9), (10), \delta(t) \in [0, 1] \end{aligned} \quad (28)$$

where θ is a parameter to be specified in Section VI. The optimal solution to (28) has the following threshold structure:

1) If $S(t) \geq \theta - \varphi V$, then $J^* = 0$, $O^* = \min \{p_B^* + \Delta p_B, O^{\max}\}$, where p_B^* is the solution to (17) and

$$\delta^*(t) = \begin{cases} 1 & \text{if } 0 \leq S(t) < \theta \\ 0 & \text{otherwise} \end{cases} \quad (29)$$

2) If $S(t) < \theta - \varphi V$, then $J^* = \min \{p_B^* + \Delta p_B, J^{\max}\}$, $O^* = \max \{0, p_B^* + \Delta p_B - J^*\}$, $\delta^*(t) = 1$.

The solution to (28) depends on the current energy level in the energy storage device without knowing any statistic information on renewable energy.

Remark 6: The detailed implementation of the proposed joint policy *FREE* can be found in Fig. 2. Although the *FREE* policy seems to be implemented separately, The proof of Theorem 9 demonstrates that the solutions to subproblems (13), (15), (17) and (28) minimize the upper bound of system Lyapunov drift plus cost function greedily. Thus, the *FREE* can solve the system optimization problem (P1) while

maintaining stability at the same time, which is formally stated in Proposition 8 and Theorem 9.

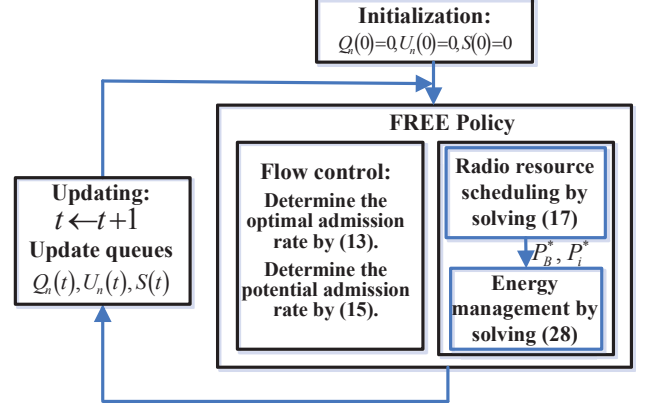


Fig. 2. The system procedure of the *FREE* scheme.

VI. ALGORITHM PERFORMANCE

This section states the properties of proposed algorithm *FREE*.

Theorem 7: For $\theta \triangleq \varphi V + O^{\max}$ and

$$0 < V \leq \frac{S^{\max} - w^{\max} - O^{\max}}{\varphi}, \quad (30)$$

the energy level in the energy storage device satisfies

$$S(t) \in [0, S^{\max}], \forall t. \quad (31)$$

Proof: The proof can be found in Appendix B. ■

The above results demonstrate that although *FREE* solves (P2) without considering the constraints (7)-(9), the energy level in storage device is feasible in each time slot. The following proposition characterizes the boundedness of data queue. By recalling (29), it is noted that θ can be regarded as a charging threshold for the battery and be implemented by the algorithm. Based on (30) and (31), the maximum V is mostly determined by S^{\max} , which should be at least larger than the summation of the maximum charging rate w^{\max} and the maximum withdrawing rate O^{\max} . We can understand the lower bound of S^{\max} by the following observation. To maintain the feasible value of residual energy in the battery, $S^{\max} \geq w^{\max} + O^{\max}$ is obtained by adding (8) and (9) together, i.e., $w(t) + O(t) \leq S^{\max} - S(t) + S(t) = S^{\max}$, $\forall t$.

Proposition 8: Initialize $Q_n(0) = 0, \forall n$. the data buffer backlogs yield the deterministic bounds $Q_n(t) \leq Q^{\max}$ for $\forall t \geq 0, \forall n$.

Proof: The proof can be found in Appendix C. ■

In the above results, given Q^{\max} the designed *FREE* can guarantee that the actual queue length is limited by Q^{\max} in each time slot and the virtual queue also has a deterministic upper bound U^{\max} . Theorem 9 further proves *FREE* designed for the relaxed problem (P2) can approach the optimal solution of original problem (P1) asymptotically.

Theorem 9: Given $Q^{\max} > A^{\max 2} + \frac{A^{\max 2} + \mu^{\max 2}}{2\epsilon}$, the proposed algorithm *FREE* can achieve the near optimal performance:

$$\liminf_{t \rightarrow \infty} \phi \sum_{n \in \mathcal{N}} f\left(\frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{R_n(\tau)\}\right) - \varphi \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{P(\tau)\} \quad (32)$$

$$\geq \mathcal{V}_1 - \frac{\Xi}{V},$$

and a bounded virtual queue

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \sum_{n=1}^N \mathbb{E}\{U_n(\tau)\} \quad (33)$$

$$\leq \frac{(\Xi + V\mathcal{V}^{\max}) Q^{\max}}{\epsilon(Q^{\max} - A^{\max}) - 2^{-1}(\mu^{\max 2} + A^{\max 2})}$$

where ϵ is a positive variable, \mathcal{V}_1 is the optimal objective value of (P1) and Ξ is defined as

$$\Xi \triangleq \frac{1}{2} N A^{\max} Q^{\max} + N \frac{Q^{\max} - A^{\max}}{Q^{\max}} A^{\max 2} \quad (34)$$

$$+ \frac{1}{2} (w^{\max 2} + O^{\max 2}).$$

Before we give the formal proof, the following lemma is needed.

Lemma 10: If the packet arrival process $\{A_n(t), \forall n \in \mathcal{N}\}$, channel state $\mathcal{I}(t)$, and renewable energy generation $w(t)$, are i.i.d., then there exists a randomized stationary policy Ψ^{RS} that takes feasible flow control, radio resource allocation and energy management only based on the current system state $\{A_n(t), \mathcal{I}(t), w(t)\}$ at every time slot t while satisfying the constraints in problem (P2) and results in the following conditions:

$$\mathbb{E}\{O^{RS}(t)\} = \mathbb{E}\{\delta^{RS}(t) w(t)\},$$

$$\mathbb{E}\{X_n^{RS}(t)\} = \mathbb{E}\{\mu_n^{RS}(t)\} = \mathbb{E}\{R_n^{RS}(t)\} = \kappa_n, \quad \forall n \in \mathcal{N},$$

$$\mathbb{E}\left\{\phi \sum_{n=1}^N f(R_n^{RS}(t))\right\} - \mathbb{E}\{\varphi P^{RS}(t)\} = \mathcal{V}_2,$$

where κ_n belongs to the network region Λ , which is the set of network capacities under all possible control policies. There also exists another randomized stationary policy RS' that only depends on the system state and the following conditions hold, $\forall n \in \mathcal{N}$.

$$\mathbb{E}\{O^{RS'}(t)\} = \mathbb{E}\{\delta^{RS'}(t) w(t)\},$$

$$\mathbb{E}\{X_n^{RS'}(t)\} = \mathbb{E}\{\mu_n^{RS'}(t)\} = \mathbb{E}\{R_n^{RS'}(t)\} = \kappa_n - \epsilon,$$

$$\mathbb{E}\left\{\phi \sum_{n=1}^N f(R_n^{RS'}(t))\right\} - \mathbb{E}\{\varphi P^{RS'}(t)\} = \mathcal{V}_{2\epsilon},$$

where $\epsilon \in \Lambda$ is a positive value that can be chosen arbitrarily close to zero. According to [38], we have $\mathcal{V}_{2\epsilon} \rightarrow \mathcal{V}_2$ as $\epsilon \rightarrow 0$.

The proof process of Theorem 9 is described in the following.

Proof: The average performance bound (32) is obtained by comparing the Lyapunov drift of *FREE* with the aforementioned randomized stationary policy. We use Lyapunov optimization technique to derive the performance bound. Let $\Theta(t) = (S(t), \mathbf{U}(t), \mathbf{Q}(t))$, where $\mathbf{U}(t) =$

$(U_n(t), n \in \mathcal{N})$, $\mathbf{Q}(t) = (Q_n(t), n \in \mathcal{N})$. Define the Lyapunov function as

$$\mathcal{L}(\Theta(t)) \quad (35)$$

$$= \frac{1}{2} \sum_{n \in \mathcal{N}} \left[\frac{Q^{\max} - A^{\max}}{Q^{\max}} U_n^2(t) + \frac{U_n(t) Q_n^2(t)}{Q^{\max}} \right] + \frac{1}{2} (S(t) - \theta)^2$$

Define the conditional Lyapunov drift as follows,

$$\Delta \mathcal{L}(\Theta(t)) \triangleq \mathbb{E}\{\mathcal{L}(\Theta(t+1)) - \mathcal{L}(\Theta(t)) | \Theta(t)\}, \quad (36)$$

where the conditional expectation is taken over the system queue. The drift of the first two items in (35) can be found in [45]. According to the battery dynamics in (7), the drift of the third item in (35) is

$$\frac{1}{2} \left((S(t+1) - \theta)^2 - (S(t) - \theta)^2 \right) \quad (37)$$

$$= \frac{1}{2} (S^2(t+1) - S^2(t) - 2\theta(S(t+1) - S(t)))$$

$$= \frac{1}{2} ((S(t) - O(t) + \delta(t)w(t))^2 - S^2(t) - 2\theta(S(t+1) - S(t)))$$

$$\leq \frac{1}{2} (w^{\max 2} + O^{\max 2} - 2(S(t) - \theta)(O(t) - \delta(t)w(t)))$$

$$= \frac{1}{2} (w^{\max 2} + O^{\max 2} - (S(t) - \theta)(p_B(t) + \Delta p_B(t) - J(t) - \delta(t)w(t)))$$

By subtracting $V \mathbb{E}\left\{\left(\sum_{n \in \mathcal{N}} \phi f(X_n(t)) - \varphi P(t)\right) | \Theta(t)\right\}$ from the conditional drift of (35), we have

$$\Delta \mathcal{L}(\Theta(t)) - V \mathbb{E}\left\{\left(\sum_{n \in \mathcal{N}} \phi f(X_n(t)) - \varphi P(t)\right) | \Theta(t)\right\} \quad (38)$$

$$\leq \Xi + \sum_{n \in \mathcal{N}} \mathbb{E}\{\Phi_{1n}(t) + \Phi_{2n}(t) - \Phi_{3n}(t) + \Phi_4(t) | \Theta(t)\}$$

$$- (S(t) - \theta) \Delta p_B(t) + \mathbb{E}\left\{\varphi V \sum_{i \in \mathcal{R}} \Delta p_i(t) | \Theta(t)\right\}$$

$$+ \frac{1}{2} \sum_{n \in \mathcal{N}} \frac{U_n(t)}{Q^{\max}} (\mu^{\max 2} + A^{\max 2})$$

where Ξ is defined in (34) and $\mathcal{R}(n)$ is the set of RSs that assist the transmissions towards user n ,

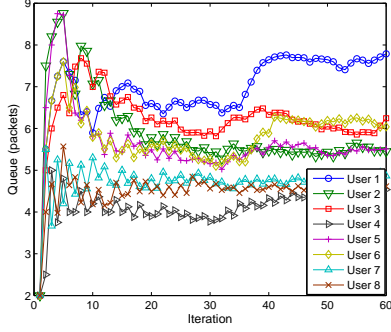
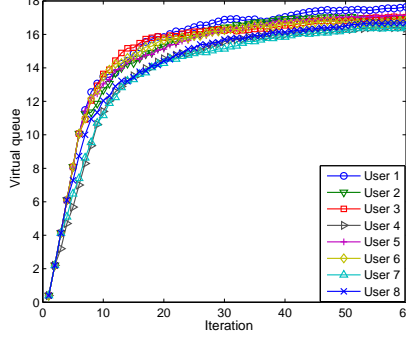
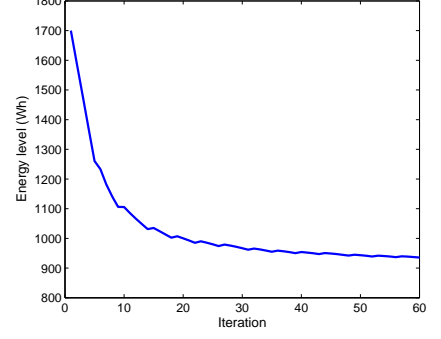
$$\Phi_{1n}(t) \triangleq \frac{Q^{\max} - A^{\max}}{Q^{\max}} U_n(t) X_n(t) - V \phi f(X_n(t))$$

$$\Phi_{2n}(t) \triangleq R_n(t) \frac{U_n(t)}{Q^{\max}} (Q_n(t) - (Q^{\max} - A^{\max}))$$

$$\Phi_{3n}(t) \triangleq \frac{U_n(t) Q_n(t) \mu_n(t)}{Q^{\max}} + (S(t) - \theta) p_B(t) - V \varphi \sum_{i \in \mathcal{R}(n)} p_i(t)$$

$$\Phi_4(t) \triangleq (\varphi V + S(t) - \theta) J(t) + (S(t) - \theta) \delta(t) w(t)$$

It can be found that the subproblems (15), (13), (17) and (28) in *FREE* minimizes $\sum_{n \in \mathcal{N}} \mathbb{E}\{\Phi_{1n}(t) + \Phi_{2n}(t) - \Phi_{3n}(t) + \Phi_4(t) | \Theta(t)\}$ on the right hand side of (38) over all possible solutions including the randomized stationary policy. Substituting the

Fig. 3. Dynamics of actual queue $\{Q_n(t)\}$.Fig. 4. Dynamics of virtual queue $\{U_n(t)\}$.Fig. 5. Energy level $S(t)$ in the storage device.

randomized stationary policy RS' into $\Phi_{1n}(t)$ and substituting policy RS into $\Phi_{2n}(t)$, $\Phi_{3n}(t)$ and $\Phi_4(t)$ on the right hand side of (38) it is obtained that,

$$\begin{aligned} & \Delta \mathcal{L}(\Theta(t)) - \mathbb{E} \left\{ \left(\sum_{n \in \mathcal{N}} \phi f(X_n(t)) - \varphi P(t) \right) | \Theta(t) \right\} \\ & \leq \Xi - \frac{\epsilon}{2} \sum_{n \in \mathcal{N}} \frac{U_n(t)}{Q_{\max}} (2(Q^{\max} - A^{\max}) \\ & \quad - \epsilon^{-1}(\mu^{\max 2} + A^{\max 2})) - V \mathcal{V}_{2\epsilon} \end{aligned}$$

If $Q^{\max} \geq \frac{\mu^{\max 2} + A^{\max 2}}{2\epsilon} + A^{\max}$, by Theorem 5.4 in [38], it is obtained that (33) and

$$\liminf_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \left\{ \sum_{n=1}^N \phi f(X_n(\tau)) - \varphi P(\tau) \right\} \geq \mathcal{V}_{2\epsilon} - \frac{\Xi}{V} \quad (39)$$

hold. Since the virtual queue $U_n(t)$ is stable by (33), we have $\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{R_n(\tau)\} \geq \lim_{t \rightarrow \infty} \frac{1}{t} \mathbb{E}\{X_n(\tau)\}$. Hence we have

$$f(\bar{R}_n) \geq f(\bar{X}_n) \geq \overline{f(X_n)}, \quad (40)$$

where the first inequality is due to the non-decreasing property of $f(\cdot)$ and the second inequality is Jensen's inequality. Note that (39) holds for all ϵ . Due to $\mathcal{V}_{2\epsilon} \rightarrow \mathcal{V}_2$ as $\epsilon \rightarrow 0$, and $\mathcal{V}_2 > \mathcal{V}_1$ we have (32) in Theorem 9 by substituting (40) into (39). ■

Remark 11: Although the designed per-slot sub-problems (13), (15), (17), (28) without considering the future network performance, jointly solve (P2) instead of (P1), the resulted solution can approach the optimal objective value of (P1) arbitrarily by regulating V . This result is reasonable since a larger storage (a larger V) can store more renewable energy to save on-grid energy to achieve a larger objective value.

Remark 12: The result in Theorem 9 is based on the assumption of i.i.d stochastic process. It can be generalized to non i.i.d. Markov modulated scenarios using the techniques developed in [38] [39].

VII. SIMULATION RESULTS

This section presents the simulation results for the proposed algorithm *FREE*. A cell with 2 km radius is considered, where eight mobile users are uniformly distributed in the cell and four RSs are assumed to be uniformly placed in the

midway of BS and cell boundary. The simulation parameters are set as follows except for other specification. In every time slot, the BS receives new packets with destinations of the corresponding users according to an i.i.d Poisson arrival process with average rate of 8 packets/s. The packet size has an exponential distribution with mean packet size of 5000 bits/packet. The buffer size for each user is 10 packets. The total bandwidth is 10 MHz with 128 subcarriers. The channel gain of any transmission pair in networks consists of a small-scale Rayleigh fading component and a large-scale path loss component with path loss factor of 4. The noise level is assumed to be 10^{-10} W and the gap to capacity is set to be 1. The static power consumption of the BS is 194.24 W and its maximum transmission power is 20 W without particular specification. For any RS, its static power consumption is 40 W and the maximum transmission power is 10 W. The power mask on each subcarrier is $\hat{P}(m) = 0.2$ W. The capacity of the BS storage device is 3000 Wh unless otherwise specified. The maximum discharge rate of the storage device is $O^{\max} = 1.5 \times (p_B^{\max} + \Delta p_B)$ W. The maximum power from the grid to supply the BS directly is $J^{\max} = O^{\max}$. The average generated solar power has two states corresponding to sunny day and cloudy day: 195 Wh with probability 0.6 and 100 Wh with probability 0.4, respectively [4]. The parameter θ is set as $\varphi V + O^{\max}$. The utility function is chosen as $f(x) = \log(1+x)$.

Firstly, we verify the stability of proposed algorithms. From Fig. 3 to Fig. 5, it is observed that all the actual queues $\{Q_n(t)\}$, virtual queues $\{U_n(t)\}$ and energy level $\{S(t)\}$ in the storage device have the trend of stability. Especially Fig. 3 shows that all actual queues are smaller than the upper bound of 10 packets and Fig. 4 demonstrates that all virtual queues are bounded, which verifies the results in Proposition 8 and (33). Fig. 5 demonstrates the results in Theorem 7 that the energy level in the storage device of the BS is always nonnegative and below the capacity of storage device.

The simulations are run for 1.2×10^4 iterations and the results in Fig. 6 to Fig. 9 are obtained by averaging the last 5000 iterations. It is shown that the time-average tradeoff value in (P1) grows with the increase of V , which verifies (32). It is further noticed that with $N = 130$ the time average objective value increases slower than that with $N = 8$, since a larger N in Ξ (34) brings a larger gap between the optimal

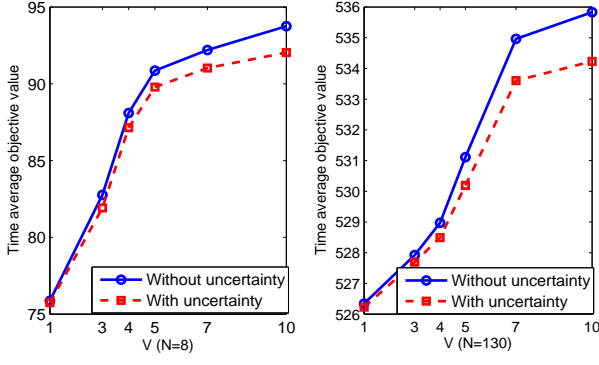


Fig. 6. Time average objective value with different V . Other parameters include $\varphi = 0.5$ and $\phi = 16$.

objective value and actual value. To decrease the gap, a larger V is needed. Fig. 6 also demonstrates that even with the same N the system objective value degrade a little when all the channel state is measured with 30% uncertainty, *i.e.* $\hat{H}(t) = H(t) + \Delta H(t)$, where $H(t)$ is the real channel gain, $|\Delta H(t)/H(t)| = 30\%$ is channel uncertainty and $\hat{H}(t)$ the measured channel gain.

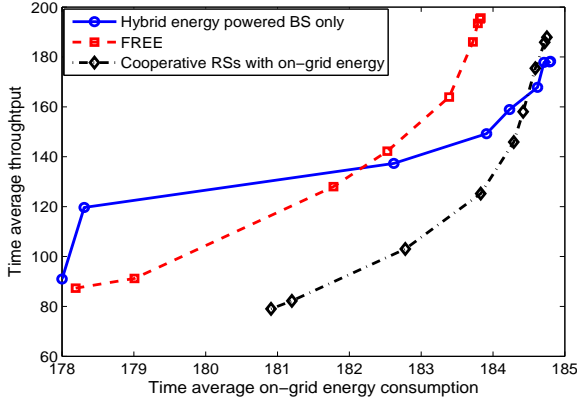


Fig. 7. The time average throughput vs time average on-grid energy consumption.

The tradeoff between the system throughput and on-grid energy consumption is shown in Fig. 7, which is depicted by decreasing φ gradually while ϕ and V are fixed. In order to measure the effects of renewable energy and cooperative relay, *FREE* is compared with the other two schemes: the scheme with hybrid energy powered BS without relay, and the scheme with both RSs and BS powered by on-grid energy alone. The compared schemes are also designed by Lyapunov optimization. In Fig. 7 it is found that for on-grid energy consumption smaller than 182 the system throughput of *FREE* is even smaller than the scheme with hybrid energy powered BS only. This range corresponds to a larger φ , which forces *FREE* to give up using most RSs to save on-grid energy. However the RSs are still there generating constant power consumption Δp_i without any throughput contribution. As φ continues to decrease, more RSs are employed by *FREE* to obtain more throughput than the scheme with hybrid energy

powered BS only. It is also found that mostly the scheme with cooperative RSs powered by on-grid energy alone is not energy-efficient compared with the other two schemes. When more on-grid energy is consumed, its throughput is larger than the scheme with BS only but still smaller than *FREE*. Thus, we can see that the benefits due to renewable energy and cooperative relay depend on proper parameter setting.

In Fig. 8 we compare *FREE* with the other two related works in [41] and [44]. Lagrange dual decomposition method and discrete particle swarm optimization method are adopted respectively by [41] and [44] for resource allocation in cooperative relay networks, *i.e.*, to pursue

$$\max \phi \sum_n f(\mu_n(t)) - \varphi P(t)$$

For fair comparison, we assume that the BSs in [41] and [44] are also powered by hybrid energy. We assume there is a heuristic renewable energy management scheme for [41] and [44]. With the heuristic scheme, the harvested energy is always charged into the battery as long as there is enough space, and the BS always uses the saved renewable energy with priority. Since the two related works do not consider flow control, we measure the time average service rate and the time average on-grid energy consumption with the decreasing φ . It is found in Fig. 8 that the performance of *FREE* outperforms the other two schemes, since it adapts the resource allocation to the arrival packets and battery states. Moreover, the performance of [44] is better than [41], since the former takes into account dynamic channel state explicitly.

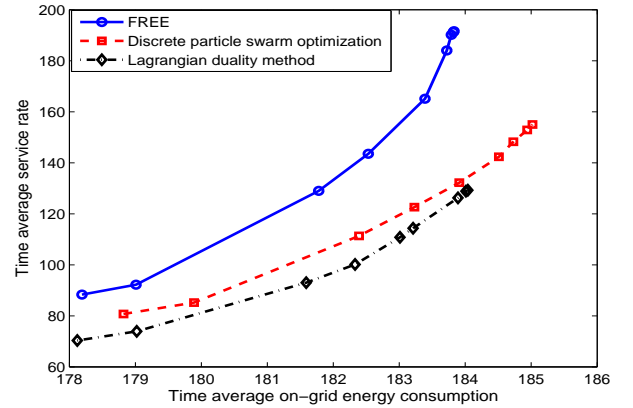


Fig. 8. Performance comparison between the proposed algorithm and the other algorithms

In Fig. 9, we use the fairness index $FI = \left(\sum_{n=1}^N \bar{R}_n \right)^2 / \left(N \sum_{n=1}^N \bar{R}_n^2 \right)$ to measure the fairness. If all users have the same throughput, FI is 1. It is found that with the number of user from 10 to 60, the proposed scheme maintains better fairness compared with the throughput maximization scheme.

VIII. CONCLUSION

In this paper, we consider to optimize the tradeoff between downlink throughput utility and on-grid energy consumption of an OFDMA cellular network with the assistance of multiple

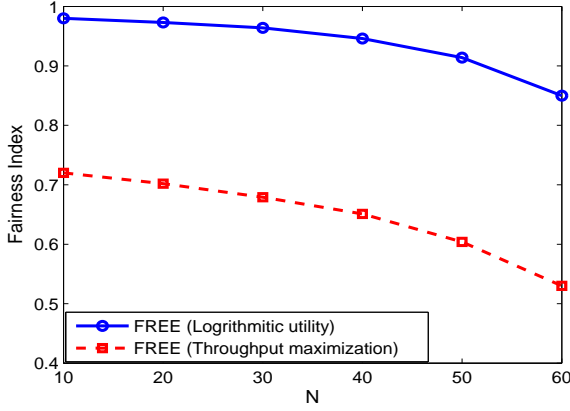


Fig. 9. Fairness index

RSs. The BS is powered by the conventional utility grid and the renewable energy. A joint design of flow control, radio resource allocation and energy management is proposed to handle the coupling between the energy consumption of the cooperative network and the storage energy allocation. The joint design scheme, namely *FREE* can be implemented by exploiting the local channel states, buffer states and energy states. Technical proof is established to ensure that *FREE* can produce a close-to-optimal performance while allowing finite data buffer and energy storage device. Simulation results show that *FREE* demonstrates better performance compared with other schemes.

APPENDIX A

1. SOLUTION TO (23)

We first pursue the solution to (23). To address the variable coupling in the objective function, we let

$$d_{i,n}^m \triangleq p_B^m H_{B,n}^m + p_{i,n}^m H_{i,n}^m. \quad (41)$$

The problem (23) is rewritten as

$$\begin{aligned} \max \quad & \Upsilon_1 = q_n(t) \log(1 + d_{i,n}^m) \\ & + \left(S(t) - \theta - \lambda_B + \frac{(V\varphi + \lambda_i)H_{B,n}^m}{H_{i,n}^m} \right) p_B^m - \frac{V\varphi + \lambda_i}{H_{i,n}^m} d_{i,n}^m \\ \text{s.t.} \quad & 0 \leq d_{i,n}^m \leq \min \{ p_B^m H_{B,i}^m, \bar{P}(m) H_{i,n}^m + p_B^m H_{B,n}^m \} \\ & 0 \leq p_B^m \leq \bar{P}(m), \end{aligned} \quad (42)$$

If $S(t) - \theta - \lambda_B + \frac{(V\varphi + \lambda_i)H_{B,n}^m}{H_{i,n}^m} \geq 0$, then the optimal transmission power of the BS over subcarrier m is $p_B^m = \bar{P}(m)$. Substituting $p_B^m = \bar{P}(m)$ into (42), the optimal $d_{i,n}^m$ is

$$d_{i,n}^m = \max \left\{ 0, \min \left\{ \tilde{d}_{i,n}^m, \bar{P}(m) H_{B,i}^m, \bar{P}(m) (H_{i,n}^m + H_{B,n}^m) \right\} \right\}$$

where $\tilde{d}_{i,n}^m = \frac{q_n(t)H_{i,n}^m}{V\varphi + \lambda_i} - 1$ is the solution to $\nabla_{d_{i,n}^m} \Upsilon_1 = 0$. Then based on the definition of $d_{i,n}^m$ in (41) the optimal $p_{i,n}^m$ is $\left(\frac{d_{i,n}^m - \bar{P}(m)H_{B,n}^m}{H_{i,n}^m} \right)^+$.

If $S(t) - \theta - \lambda_B + \frac{(V\varphi + \lambda_i)H_{B,n}^m}{H_{i,n}^m} < 0$, then the optimal solutions to (42) are $p_B^m = 0$ and $d_{i,n}^m = 0$ and then $p_{i,n}^m = 0$.

2. SOLUTION TO (24)

Let the objective of (24) be Υ_2 . Since the objective function of (24) is decreasing with respect to $p_{i,n}^m$, the optimal value is

$p_{i,n}^m = 0$. There are two cases to be considered for the optimal p_B^m . If $H_{B,i}^m > H_{B,n}^m$, then the optimal transmission power of the BS is $p_B^m = 0$. If $H_{B,i}^m \leq H_{B,n}^m$, the optimal value is

$$p_B^m = \begin{cases} \bar{P}(m) & \text{if } S(t) - \theta - \lambda_B \geq 0 \\ \left(\frac{q_n(t)}{\lambda_B - S(t) + \theta} - \frac{1}{H_{B,i}^m} \right) \bar{P}(m) & \text{otherwise} \end{cases},$$

where the optimal p_B^m in the case of $S(t) - \theta - \lambda_B < 0$ is obtained by solving $\nabla_{p_B^m} \Upsilon_2 = 0$ considering the power mask and non-negative constraints.

APPENDIX B PROOF OF THEOREM 7

We now use the induction method to derive (31). Initially, without any action on the storage device, $0 \leq S(0) \leq S^{\max}$ holds. Supposing (31) holds for time slot t , we will prove it holds for slot $t+1$. There are the following three cases to be considered.

i) If $0 \leq S(t) < O^{\max}$, then

$$\begin{aligned} & S(t+1) \\ &= S(t) + \delta^* w(t) - O^*(t) \\ &= S(t) + w(t) - \max\{0, p_B^*(t) + \Delta p_B(t) - J^*\} \\ &= S(t) + w(t) \geq 0 \end{aligned} \quad (43)$$

where δ^* and $O^*(t)$ are derived from solving (28). Due to $\theta \triangleq \varphi V + O^{\max}$, it falls into the second situation of the solution to (28).

Next we show that $S(t+1) \leq S^{\max}$. By (7), we have

$$S(t+1) < S(t) + w^{\max} < O^{\max} + w^{\max} \quad (44)$$

By substituting the upper bound of V (30) into (44), we have

$$S(t+1) < S^{\max} - V\varphi < S^{\max}$$

ii) If $O^{\max} \leq S(t) < S^{\max} - w^{\max}$, we have

$$S(t+1) = S(t) + \delta^* w(t) - O^*(t) \geq O^{\max} - O^*(t) \geq 0.$$

Moreover,

$$\begin{aligned} S(t+1) &\leq S(t) + w^{\max} \\ &< S^{\max} - w^{\max} + w^{\max} = S^{\max} \end{aligned}$$

iii) If $S^{\max} - w^{\max} \leq S(t) \leq S^{\max}$, it means $S(t) \geq \theta$, which is obtained by substituting the upper bound of V (30) into $\theta \triangleq \varphi V + O^{\max}$. Thus, we have $\delta^* = 0$ and

$$\begin{aligned} S(t+1) &= S(t) + \delta^* w(t) - O^*(t) \\ &> S^{\max} - w^{\max} - O^{\max} > 0. \end{aligned} \quad (45)$$

$$\begin{aligned} S(t+1) &= S(t) + \delta^* w(t) - O^*(t) \\ &= S(t) - O^*(t) < S^{\max}. \end{aligned}$$

To summarize, $S(t+1) \in [0, S^{\max}]$ holds if $S(t) \in [0, S^{\max}]$.

APPENDIX C PROOF OF PROPOSITION 8

$Q_n(0) = 0 < Q^{\max}$. Supposing that $Q_n(t) \leq Q^{\max}$, we have two cases. (a) $Q_n(t) \leq Q^{\max} - A^{\max}$. Obviously, $Q_n(t+1) \leq Q_n(t) + A^{\max} \leq Q^{\max}$ according to the

dynamics of (6). (b) If $Q_n^{\max} \geq Q_n(t) > Q_n^{\max} - A^{\max}$, then $R_n(t) = 0$ according to (14). Thus, we have $Q_n(t+1) \leq Q_n(t) \leq Q_n^{\max}$.

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